MORPHOMETRIC SEX IDENTIFICATION AND FORENSIC FACIAL SOFT TISSUE THICKNESS ASSESSMENT IN THE INDIAN POPULATION: A CBCT BASED STUDY USING ARTIFICIAL NEURAL NETWORKS

Dr. JIJIN MJ

UIN: 1805002010

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INTRODUCTION

Personal identification is very important for unknown remains after natural disasters and man-made disasters including tsunamis, earthquakes, floods, landslides, terrorist attacks, mass murders, or bomb blasts. Personal identification is imperative when a body is purposely dismembered in a manner that may conceal the identification[(1)].

Identification of an unknown individual by sex identification, age, and ethnicity play a crucial role in forensic medicine. Sex identification remains a crucial aspect of identifying unknown human remains in forensic medicine, especially when it is not possible to retrieve whole skeletons or remains for analysis.

The primary methods of identification include fingerprint analysis, DNA, and forensic odontology, while the secondary methods include a personal description of the missing person, anthropological information, circumstantial evidence, documentation, and medical procedures performed[(2)]. Forensic anthropology is the method of choice for identifying an individual in cases of decomposed or charred bodies, destroyed DNA, and when there are no previous dental records[(3)].

After death, skull is the most commonly preserved part of the skeleton and hence in many cases, it is the only available part for forensic examination. In the past few years, there have been a rise in the number of criminal cases, especially involving murders and burning of body. In cases where facial features are fully distorted, that identification of the deceased possess a challenge to the forensic experts.

Gender determination plays a crucial role in medicolegal cases especially in cases of natural calamities, mass disasters or crime scenes when body is decomposed

and fragmented. The accurate prediction of the sex of unknown skeletal remains would narrow down the field of possible identifications to ½ of the sample, thereby shortening the work of anthropologist by narrowing the amount of antemortem records to be retrieved for comparison with the unknown remains.

Evidence from different studies have reported differences in the shape and size of maxillary sinuses of males and females in various population[4-6]. Studies assessing the correlation of frontal sinus and gender has demonstrated smaller frontal sinus in women compared to males[7].

Radiography has been used in forensic odontology especially in cases when the body is decomposed, fragmented, or burned. Radiographic analyses have been used commonly in assessing age, gender, in locating foreign objects such as projectiles and their wound paths, in evaluating fragmentary remains of the skull and other body parts. Cone beam computed tomography (CBCT) is the generation next imaging modality that has various technical and practical features that are superior to conventional CT and also exhibits lesser metallic artifacts with easier portability.

Further facial reconstruction is an effective forensic technique used to recreate a victim's facial appearance from the skull. Facial reconstruction is based on the relationship between the underlying hard tissues and soft tissues. With the recent advancements in technology, the accuracy and validity of facial reconstruction has been improved and has been extensively used by law enforcement agencies[8]. The advent of artificial intelligence (AI) has brought new robustness to forensic medicine. AI techniques offer an objective and reproducible solution for sex determination. Artificial neural networks automatically discover the features of an image that are

most useful for classification and automatically de-emphasize the parts of the image that are not useful[9].

To the best of our knowledge, this is the first study reporting sex determination utilizing artificial neural network in the Indian population. The primary aim of this study is to determine the sex based on paranasal sinus measurements. The secondary objective is to determine the sex of patient based on the facial thickness and neural network techniques utilizing CBCT acquired images.

AIMS AND OBJECTIVES

- The primary aim of this study is to determine the sex based on paranasal sinus measurements and neural network techniques from CBCT acquired images.

- The secondary objective is to determine the sex of patient based on the facial thickness and neural network techniques utilizing CBCT acquired images.

HYPOTHESIS

We hypothesize that artificial neural network can perform sex determination based on skeletal structures and facial thickness.

REVIEW OF LITERATURE

Human skeletal remains can be used for identification of height, age, race, and sex that are considered the four fundamental elements of forensic science and physical anthropology. Sex determination plays an important role in identifying the subject in forensic medicine. As paranasal sinuses remain intact even after severe damage to the skull and other bones, these are used in the gender identification in forensics. CBCT is a brilliant diagnostic tool in the examination of paranasal sinuses.

RADIOGRAPHIC STUDIES REPORTING THE ROLE OF PARANASAL SINUSES MEASUREMENTS IN SEX DETERMINATION

The systematic review by Sridhar M and colleagues reported males to have significantly higher values for frontal sinus and maxillary sinus compared to females in terms of length and width for frontal sinus and in terms of length, width and volume for maxillary sinus. From their analysis it was evident that there are variations among the different population[(10)].

The radiographic study by Wanzeler et al revealed female subjects to have smaller volumes of the maxillary, frontal and sphenoidal sinuses ($p < 0.001$). From their study, it was noted that the chances to identify gender in males was higher compared to females based on paranasal sinus volumes (96.2% and 92.7% for males and females respectively). Further correlating these values with foramen magnum measurements yielded sex identification in 100% of study population[(11)].

STUDIES REPORTING THE ASSESSMENT OF FACIAL THICKNESS USING CBCT

Facial approximation plays an important role in personal identification and the study on facial soft tissue thickness (FSTT) is important to allow more accurate facial approximation. Facial approximation is performed especially in cases where it is difficult to identify facial features. Facial reconstruction is a specialized forensic technique to identify the deceased from the unknown skull. It is dependent on population-specific facial soft tissue thicknesses.

The study by Manasa and Chaya demonstrated the application of CBCT in facial soft tissue thickness measurements for craniofacial reconstruction. Their descriptive study aimed to propose the mean dataset of facial soft tissue thickness for South Indian population by utilizing CBCT. Further the study also evaluated the differences in sex and race in terms of facial soft tissue thickness values if any. In their study males had thicker soft tissue than females in most of the landmarks. Differences in the bilateral soft tissue thicknesses were negligible. Indians had thicker facial tissues than the Koreans and CBCT was found efficient in measuring soft tissue thickness[12].

Sahni et al has reported the facial soft tissue thickness in northwest Indian adult population. The facial soft tissue thickness was determined at 29 standard anthropological landmarks by MRI in 173 male and 127 female adult subjects of northwest Indian origin. A stepwise discriminant function analysis selected nine landmarks for better sex classification in facial soft tissue thickness measurements. The thickness of soft tissue was different from those reported in literature and also for those samples from other countries. There was a correlation between skinfold thickness and body mass index with facial soft tissue thickness. The data of facial soft tissue thickness will help forensic experts in reconstructing the face from a skull for identification purposes.

METHODOLOGY

This was a cross-sectional study based on the CBCT scans obtained from nationwide imaging centers. The study focused on adult patients who had undergone CBCT scan for different head and neck diagnosis. The study was registered prospectively on clinical trials registry – India with CTRI NUMBER:CTRI/2020/08/027010[REGISTERED ON:7/8/2020]. A detailed protocol explaining the purpose and procedures of the study was approved by the Institution Review Board, Sri Balaji Vidyapeeth University. The study was initiated after obtaining ethical clearance (IECSHST-03/MDC/2020).

The final analysis of this study included 450 CBCT scans obtained over a period of 32 months (between 30th July 2020 and 25th March 2023) from different imaging centres from all over India. The sample size was determine during the below formula keeping the significance alpha (a)=0.05, estimated proportion (p)=(100-p)[12] [when p is in percentage terms] and0.12[when p is in decimal terms], the precision of estimate (d)=0.03, and prevalence (P)=88% taken with reference to previous study[13]; the sample size was determined to be 450 using the formula.

$$n=Z^2 1\text{-}a/2 \frac{P(1-P)}{d^2}$$

The study population for this final report included all adult patients who had undergone CBCT scanning for different diagnosis during the study period. The population was divided into five intervals for the investigation of soft tissue thickness and sinus volume measurements in various age groups (18–28,29–39,40–50,51–61,62–72,>73).

Data collection

All the CBCT scans were observed on Newton machine (Giano HR CBCT machine) using CBCT scanner with NMT software. The CBCT scans were made with a matrix size of 16 x 18FOV, 90kvp, 6mA and exposure time of 1.0 seconds.

Inclusion criteria

1. CBCT images of subjects aged above 18 years who were referred for CBCT evaluation of the head and neck region.

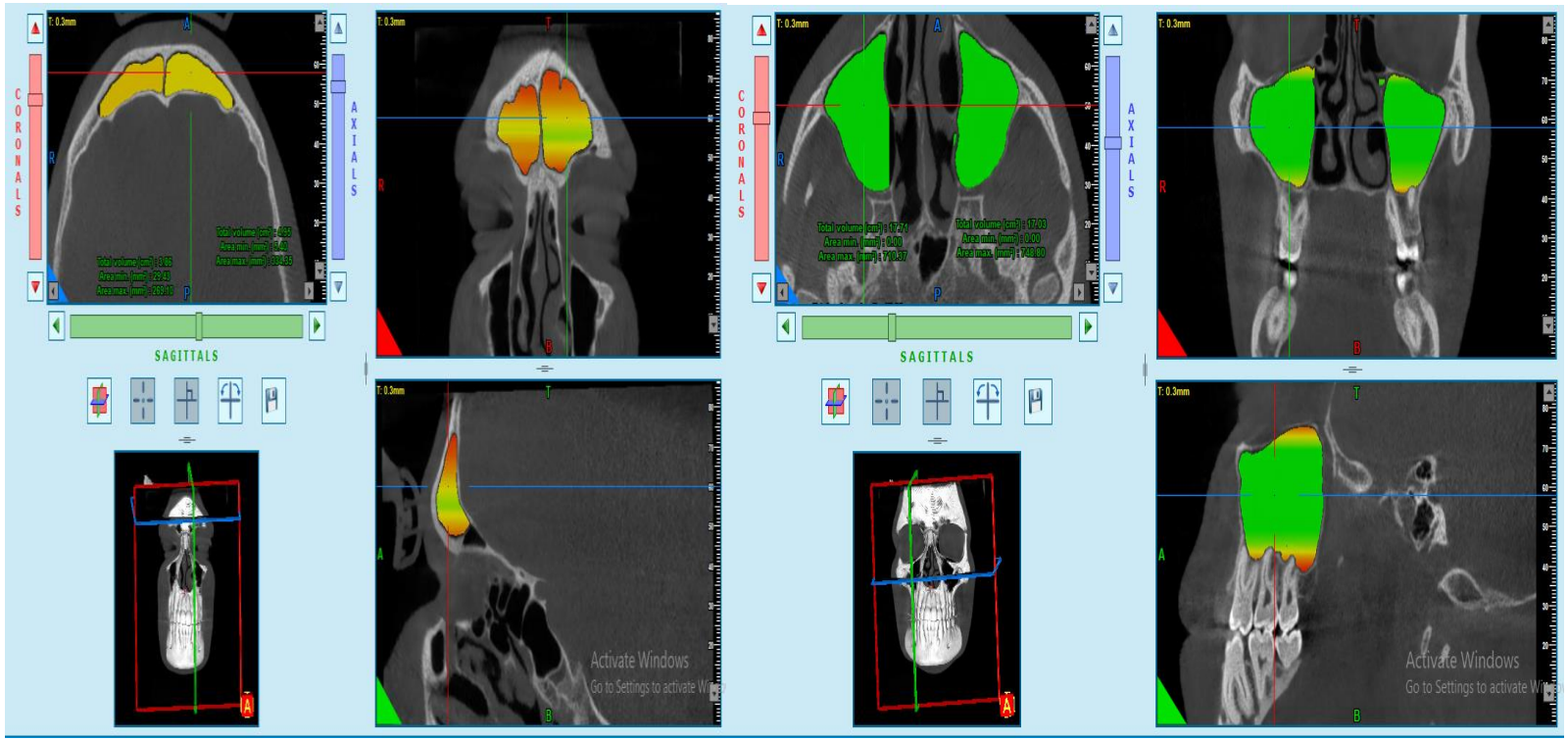
2. CBCT images without any artefacts or distortions.

Exclusion criteria

1. CBCT images with facial trauma, evidence of sinus pathology or previous surgery.
2. Distorted images or images with artefacts.

Gender Identification

Based on certain anatomical landmarks, the maxillary sinus and frontal sinus measurements were performed in the axial sections of CBCT images. The volumetric analysis of the maxillary and frontal sinuses was performed using the volumetric analysis tool. The segment base structures were delimitated by the examiner in the multiplanar reconstructions, defining the region of interest for segmentation (**Figure 1**).



A] FRONTAL SINUS **B] MAXILLARY SINUS**

Figure 1: Frontal and Maxillary Sinuses Volume in axial, sagittal, coronal view

FSTT Assessment

Facial soft tissue thickness measurements were made in millimetres, by following the methodology described by **Cavanagh and Steyn**.

Measurements were taken with the Image Tool of the CBCT scan program Centricity to the nearest tenth of a millimetre. The method of soft tissue measurement was similar to that described by D. Cavanagh et al.,(14) and was established as follows: a tangential line was drawn to the curve of the outer surface of the bony landmark (line 1 in **Figure 2**). A line was drawn perpendicular to the tangent at the bony landmark and extended outward to meet the facial profile (line 2 in **Figure 2**). The length of the line from the bone to the junction with the skin surface was regarded as the equivalent STT at that landmark (**Figure 2**).

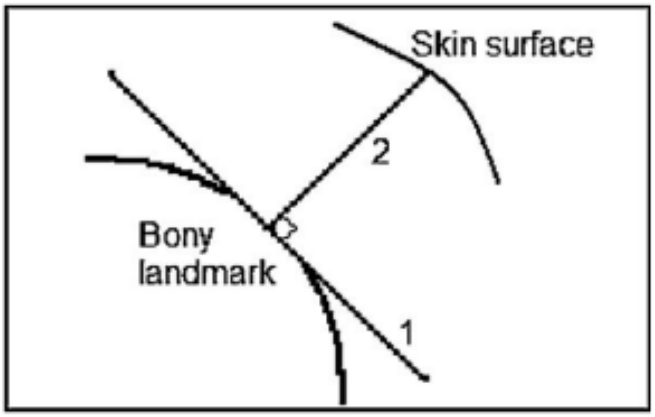


Figure 2. Diagrammatic representation of establishing tissue thickness measurements

28(12 midline points and 16 lateral points) facial thickness measurements were performed in different order, with a 3-day space for every three images to diminish intra-observer and interobserver errors. Images of some of the midline and lateral points are presented in **Figure 3**. Intra-observer agreement was statistically analyzed on repeat measurements of five randomly selected subjects, measured on two

occasions with paired t-test. Inter-observer reliability was statistically analyzed on repeat measurements of one selected subject made by an independent observer and the investigator with paired t-test.

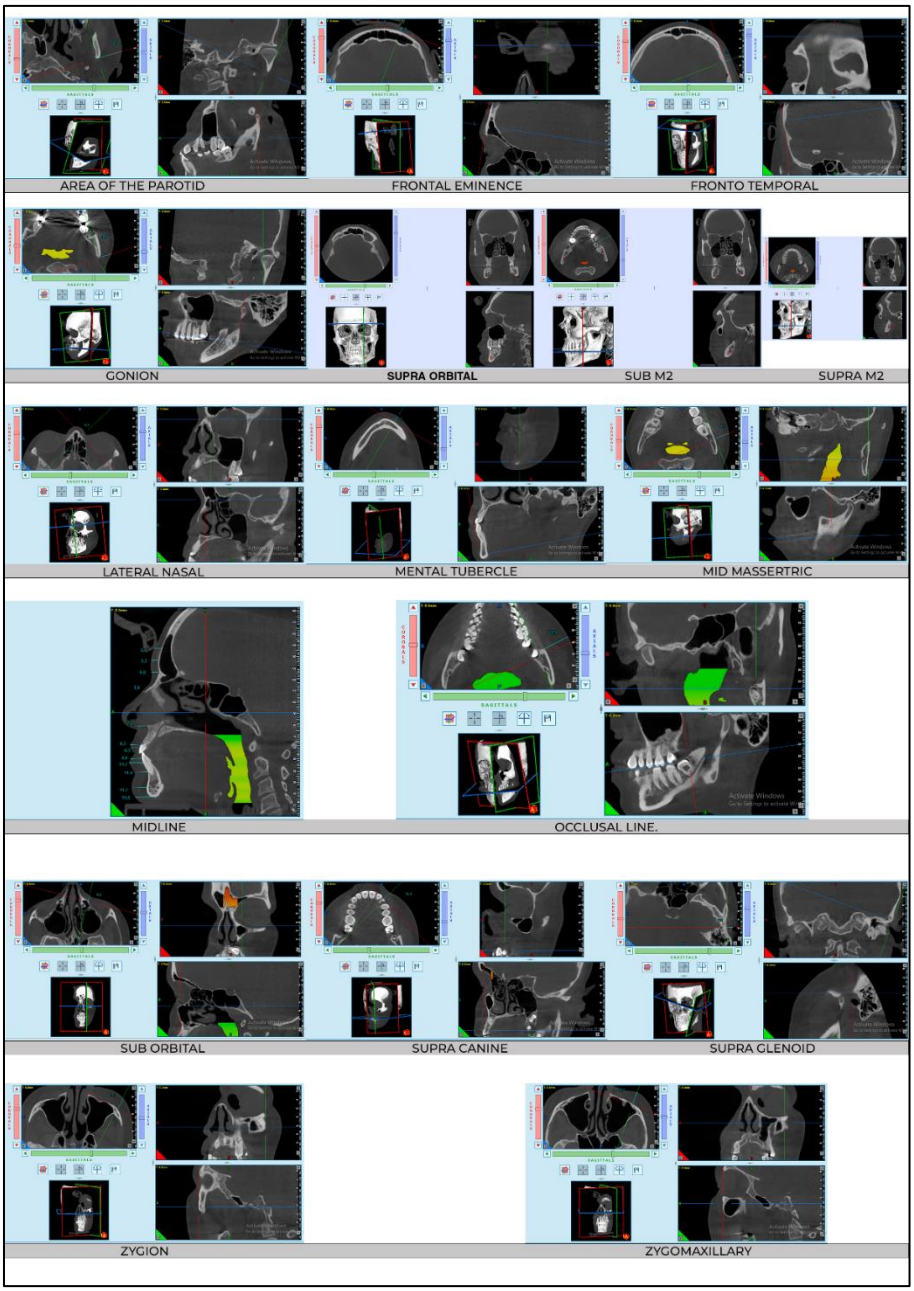


Figure 2: Midline and Lateral Landmarks on the CBCT images

Neural Networks

Set of algorithms, models loosely based on the human brain were designed to recognize patterns. Patterns recognized included numerical and those contained in vectors.

Artificial neural network (ANN)

ANN consist of neurons that are connected by link, each of which has a numerical weight. A feed-forward neural network with back propagation learning algorithm is a useful technique consisting of one input layer, one output layer, and a number of hidden layers. The sigmoid and linear functions are usually adopted as the activation functions on the hidden and output layers for this kind of network, respectively.

In order to train the network, the input data are received via the input layer and distributed to the hidden layers. Neurons in the hidden layers detect the information via their weights, perform the calculation according to the corresponding activation function and then propagate the output signal to the next layers.

Neural Network with Back Propagation Architecture

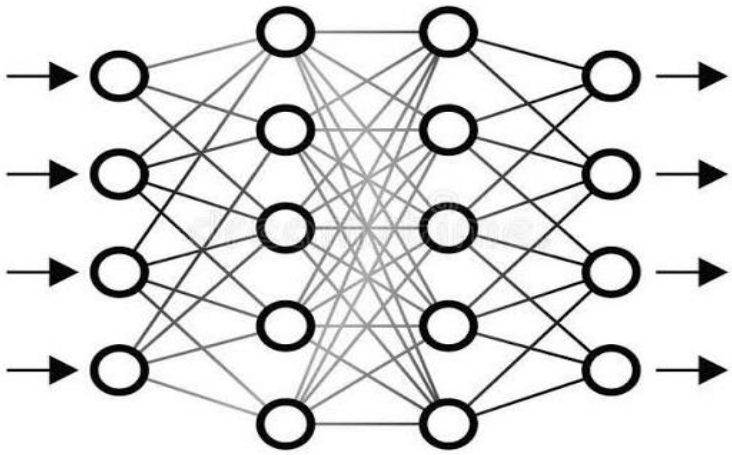
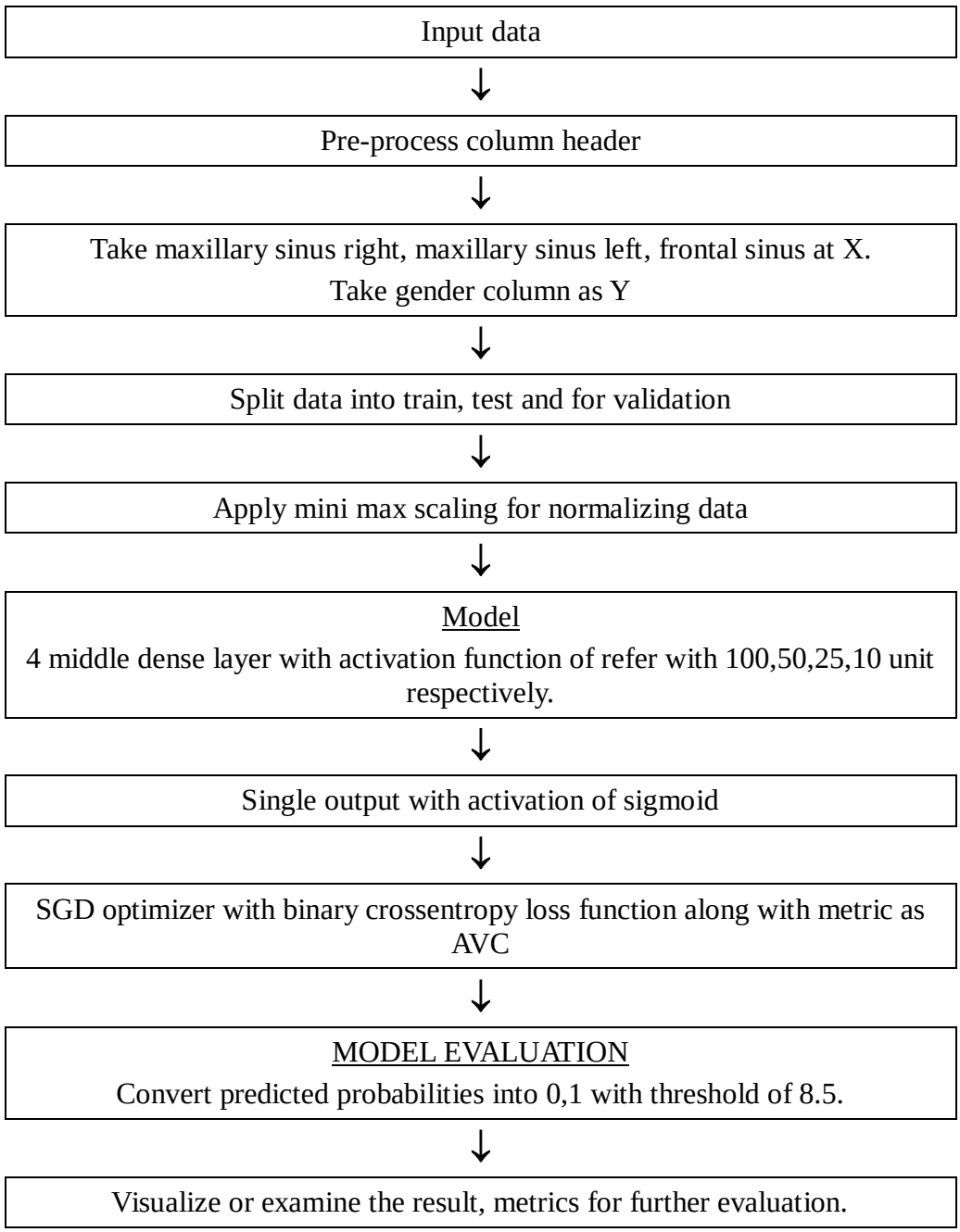


Figure 3: Neural network with back propagation architecture

Model -1. This is a standard ANN architecture where inputs with 3 features are fed through a series of fully connected Layers, namely 4 Dense layers and finally a binary output layer is obtained. The activation functions for all the hidden layers are ReLu and for the output layer a sigmoid activation function is used. The loss function used for the model is binary cross entropy and training was done on a dataset of certain datapoints. This is a classic example of supervised learning through deep learning models.

Model:1


Input data
Pre-process column header
Take maxillary sinus right, maxillary sinus left, frontal sinus at X.
Take gender column as Y
Split data into train, test and for validation
Apply mini max scaling for normalizing data
Model
4 middle dense layer with activation function of refer with 100,50,25,10 unit respectively.
Single output with activation of sigmoid
SGD optimizer with binary crossentropy loss function along with metric as AVC
MODEL EVALUATION
Convert predicted probabilities into 0,1 with threshold of 8.5.
Visualize or examine the result, metrics for further evaluation.

Model-2

This is a variation of the ANN model where multiple outputs are defined to be originated from the parent network. Like the previous model, a 3-feature input layer is connected to 4 FC layers which branch out to two different outputs, a categorical output as well as a binary output. The output layer `age_grp_out` is of categorical type and hence has a loss function of categorical cross entropy with the output layer activation being SoftMax activation, whereas the output layer `gender_out` is of a binary type and has a loss function of binary cross entropy with an activation function of sigmoid.

MODEL 2

Input data

↓

Pre-process column header

↓

Take maxillary sinus right, maxillary sinus left ,frontal sinus at X.
Take gender column as Y

↓

Split data into train, test and for validation

↓

Apply mini max scaling for normalizing data

↓

MODEL

- 4 middle dense layers with activation function as refer with units of 100,50,25,10 respectively
- Two output neurons, one for age group and one for gender with activation of soft tissue and sigmoid respectively.
- Concentrate the two output and build the model
- Complete the model with optimizer as SGD and two loss function, one for age groups and (cross entropy) and other for gender(binary cross entropy)along with metrics as “accuracy”

↓

MODEL EVALUATION

↓

Convert predicted values of age group into appropriate categories and convert gender predicted values into 0,1 with threshold 0.5.

↓

Visualize, examine the history of model for further improvement.

ANN PREDICTION- VALIDATION SET

The volumetric measurements were subjected for gender predictions. ROC was plotted, and AUC was determined to identify the best predictor of gender amongst the CBCT parameters of maxillary and frontal sinus. ROC/AUC Model 1 showed 72% accuracy on the experimental data set what we have. Model 2 is likely to be 99% accuracy prediction on the experimental data set what we have. ANN exhibited a higher accuracy and revealed a good gender prediction tool.

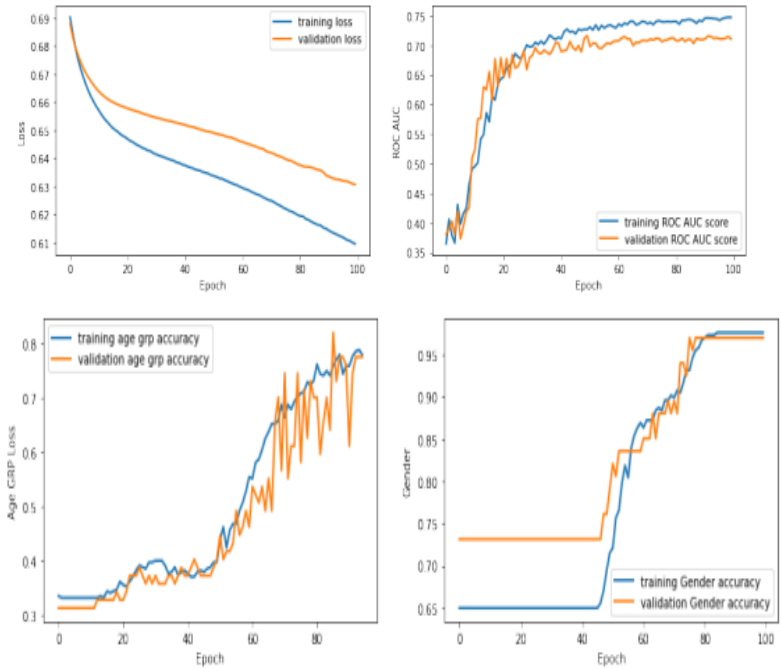


Figure 4: Ann Prediction- Validation Set

STATISTICAL ANALYSIS

All the statistical analysis was carried out using Statistical Package for the Social Sciences (SPSS) software (Version 22.0, IBM Corp, USA). The inter-observer variability was evaluated using Intra Class Correlation coefficient (ICC) for the entire study sample. Student's t-test was performed for comparisons between genders.

Discriminant Analysis

The discriminant analysis was performed to examine the significant differences which existed in predicting gender by the predictor variables. Gender was taken as criterion variables (male/female) and the predictor variables were parameters measured on CBCT.

Canonical Discriminant Function Coefficients describe the contribution of independent variables to the discriminate function.

The structure matrix shows the relative importance of the predictors in the model in terms of correlations of each variable with the discriminate function. In this analysis, 0.30 was taken as cut-off between important and less important variables. The linear and volumetric measurements were subjected for gender predictions with ANN. McNemars test was carried out to find the differences between the actual gender and predicted gender by ANN.

RESULTS

Baseline Characteristics

The study participants included 450 subjects with a mean age of 37.34 ± 15.43 years for males and 37.50 ± 14.68 years for females respectively.

The mean maxillary sinus measurement was significantly higher for males as compared to females (19.38 ± 6.67 vs 14.34 ± 3.78; $p \leq 0.05$). The mean maxillary sinus measurement was 17.62±5.38 for males and 15.62±3.85 for females on right side, while left side maxillary sinus had a measurement of 18.60±8.94 for males and 15.73±3.82 for females.

Also, a significantly higher frontal sinus measurement was noted in males compared to females (9.41±5.05 vs 5.72±3.44respectively; $p \leq 0.05$). The nasion, rhinion, lateral nasal,mid upper lip margin, upper incisor, mid lower lip margin, lower incisor, mental tubercle, mental eminence, menton, fronto-temporale, supra-orbital, gonion, supra M2,sub M2, occlusal line and mid masseteric measurements were significantly higher for males compared to females. Differences of ≥ 1 mm was observed between males and females at maxillary sinus, frontal sinus, nasion, rhinion, lateral nasal, mid upper lip margin, upper incisor, mid lower lip margin, lower incisor, mental eminence, menton, fronto-temporale, mid masseteric, supra-orbital, gonion, supra M2, sub M2, occlusal line and mid masseteric measurements (**table 2**).

Table 1: Sex based comparison of anatomical facial landmarks

Measurement Variable	Gender	N	Mean	Std. Deviation	*p* value
Maxillary sinus right	Males	158	17.62	5.38	$p \leq 0.05$
	Females	292	15.62	3.85	
Maxillary sinus left	Males	158	18.60	8.94	$p \leq 0.05$
	Females	292	15.73	3.82	
Frontal sinus	Males	158	9.41	5.05	$p \leq 0.05$
	females	292	5.72	3.44	
Supra glabella	males	158	5.40	0.95	$p \geq 0.05$
	females	292	4.86	0.90	
Glabella	males	158	5.33	1.04	$p \geq 0.05$
	females	292	4.91	0.88	
Nasion	males	158	7.38	1.51	$p \leq 0.05$
	females	292	5.94	1.05	
Rhinion	males	158	2.75	1.06	$p \leq 0.05$
	females	292	2.43	0.77	
Lateral nasal	males	158	5.83	2.22	$p \leq 0.05$
	females	292	4.65	1.40	
Supra- canine	males	158	10.94	2.14	$p \geq 0.05$
	females	292	9.10	1.97	
Mental tubercle	males	158	11.07	2.50	$p \geq 0.05$
	females	292	9.24	2.21	
Mid-philtrum	males	158	11.88	3.16	$p \geq 0.05$
	females	292	10.69	2.56	
Mid upper lip margin	males	158	10.60	2.69	$p \leq 0.05$
	females	292	9.36	2.02	
Upper incisor	males	158	7.81	2.67	$p \leq 0.05$
	females	292	6.25	1.80	
Mid lower lip margin	males	158	13.38	2.84	$p \leq 0.05$
	females	292	12.10	2.06	
Lower incisor	males	158	10.30	2.91	$p \leq 0.05$
	females	292	9.22	2.21	
Supra-mentale	males	158	12.06	1.83	$p \geq 0.05$
	females	292	11.55	7.75	
Mental eminence	males	158	12.13	2.73	$p \leq 0.05$

	females	292	10.71	2.29	
Menton	males	158	15.10	3.41	$p \leq 0.05$
	females	292	13.09	2.77	
Frontal eminence	males	158	5.24	1.33	$p \geq 0.05$
	females	292	4.66	1.29	
Fronto-temporale	males	158	8.47	2.10	$p \leq 0.05$
	females	292	6.97	1.80	
Supra-orbital	males	158	8.71	2.07	$p \leq 0.05$
	females	292	8.02	1.50	
Sub- orbital	males	158	5.69	1.75	$p \geq 0.05$
	females	292	5.21	1.61	
Zygomaxillare	males	158	9.07	3.40	$p \geq 0.05$
	females	292	8.73	3.26	
Lateral zygomatic arch	males	158	8.38	2.14	$p \geq 0.05$
	females	292	8.92	2.23	
Supra-glenoid	males	158	12.23	2.93	$p \geq 0.05$
	females	292	11.76	2.42	
Area of the parotid	males	158	22.60	4.24	$p \geq 0.05$
	females	292	19.96	3.86	
Mid masseteric	males	158	23.50	4.10	$p \leq 0.05$
	females	292	20.30	3.28	
Gonion	males	158	18.24	4.91	$p \leq 0.05$
	females	292	15.71	4.45	
Supra M2	males	158	27.56	4.74	$p \leq 0.05$
	females	292	25.80	3.83	
Sub M2	males	158	26.47	4.59	$p \leq 0.05$
	females	292	24.47	3.78	
Occlusal line	males	158	25.37	3.97	$p \leq 0.05$
	females	292	23.08	3.32	

The variables which showed statistically significant differences ($p<0.05$) were included in discriminant analysis namely maxillary sinus, frontal sinus nasion, mental tubercle, mid upper lip margin, upper incisor, menton, fronto-temporale, and mid masseteric measurements. Stepwise analysis was done, and the final model consisted

of only three variables which gave the least Wilk's lambda value namely frontal sinus, mid upper lip margin and nasion. In the present study, the Box's M is 35.959 with F = 5.537 which is significant at $p<0.001$ which showed that the groups do not have equal covariance matrices. The canonical discriminant function coefficients showed that the nasion measurement contributed high in predicting gender followed by frontal sinus and mid upper lip margin (supra dentale or alveolare). In the present study, the canonical correlation was 0.695. It indicates that only 48% of the variance in the grouping variable is explained by this model.

The present study shows a Wilk's Lambda of 0.517 indicating a highly significant discriminate function ($p<0.001$). It also provides the proportion of total variability not explained by the model i.e., 52%. The discriminant function coefficients were used to assess each independent variable's unique contribution to the discriminate function. In the present study, step wise method was used and only three variables were significant in the model, namely frontal sinus, mid upper lip margin and nasion. Discriminant function = -7.950 + 0.298 (Frontal sinus) + 0.229 (Mid Upper lip margin) + 0.639 (Nasion), **table 3.**

Table 2 Discriminant function coefficient value of frontal sinus, mid upper lip margin and nasion

Variables	Discriminant function coefficient value
Frontal sinus	0.298
Mid upper lip margin (supra dentale or alveolare))	0.229
Nasion	0.639
Constant	-7.950

The cut off score was calculated as the mean of the group centroids which was 0.021. The discriminant scores above the cut off value was predicted as females and the discriminant scores below the cut off value was predicted as males. The male sex was predicted correctly up to 72.7% and female sex up to 87%

Figure 5 is the graphical representation depicting change in the trend in STT with the advancing age of males and females. The males had significantly thicker, soft tissues than the females at almost all landmarks.

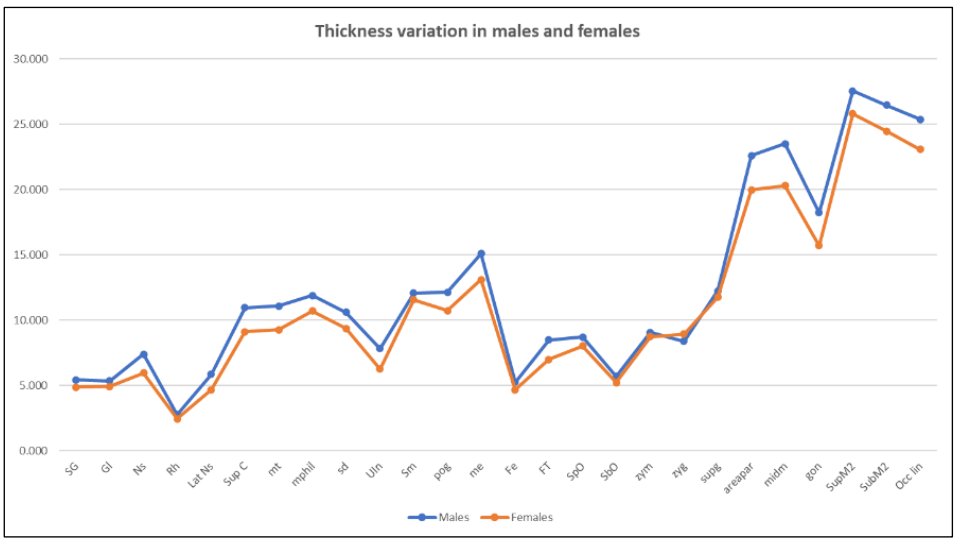


Figure 5: Graph showing gender-based differences in facial soft tissue thickness

The Bonferroni post hoc test revealed the statistically significant difference in the means of anatomical landmark between different age groups in males and females ($p \leq 0.05$). In males, there was a significant difference in the means of supracanine anatomical landmark between the age groups18 -28 yrsand62-72yrs, 18 -28 yrs and >73yrs, and29-39 yrs and>73yrs.As age increases, the means of supracanine anatomical landmark decreases ($p \leq 0.05$). The mean of mental tubercle was statistically higher for older age group (51-61yrs) as compared to the younger age group 18 -28 yrs ($p \leq 0.05$). For menton, the means was significantly higher for the age groups51-61yrs as compared to 18 -28 yrs ($p \leq 0.05$). In the area of parotid, there was a significant difference in the means between the age groups 18 -28 yrs and 29-39 yrs, 18 -28 yrs and 40-50yrs, and 18 -28 yrs and 51-61yrs ($p \leq 0.05$). For mid masseteric landmark, there was a significant increase in the means from a younger age group (18 -28 yrs) to older age group (29-39 yrs; 40-50yrs) ($p \leq 0.05$).There was a significant difference in the means of gonion anatomical landmark between the age groups 18 -28 yrs and 29-39 yrs, 18 -28 yrsand40-50yrs, 18 -28 yrs and 51-61yrs, 18 -28 yrs and 62-72yrs, and 29-39 yrsand 40-50yrs.For sub M2, the means increased significantly from the age group 18 -28 yrs to 40-50yrs ($p \leq 0.05$).There was a significant increase in the means of occlusal anatomical landmark from the age group 18 -28 yrs to 29-39 yrs, and from 18 -28 yrs to 40-50yrs ($p \leq 0.05$).

For females, there was a significant increase in the means of supraglabella anatomical landmark from the age group 18 -28 yrs to 51-61yrs, and 29-39 yrs to 51-61yrs ($p \leq 0.05$).There was a significant difference in the means of glabella anatomical landmark between the age groups 29-39 yrs and 51-61yrs ($p \leq 0.05$). For the supracanine landmark, the means decrease significantly from the younger age group (18 -28 yrs) to older age group (29-39 yrs; 40-50yrs; 51-61yrs) ($p \leq 0.05$).There

was a significant difference in the means of mental tubercle anatomical landmark between the age groups 18 -28 yrs and 29-39 yrs, 18 -28 yrs and 51-61yrs, and 40-50yrs and 51-61yrs ($p \leq 0.05$).The means of mid upper lip margin decrease significantly between the age groups 18 -28 yrs and 51-61yrs ($p \leq 0.05$). For the supra-mentale, there was a significant increase in the means from the younger age groups 18 -28 yrs to 51-61yrs, 29-39 yrsto 51-61yrs, and 40-50yrs to 51-61yrs ($p \leq 0.05$). For mental eminence, the means of increase significantly between the age groups 18 -28 yrs to 51-61yrs ($p \leq 0.05$).There was a significant increase in the means of menton anatomical landmark from the age group 18 -28 yrs to 51-61yrs.The means of supraorbital anatomical landmark increases significantly from the age group 18 -28 yrs to 40-50yrs, 18 -28 yrs to 51-61yrs, 18 -28 yrs to 62-72yrs, and 18 -28 yrs to >73yrs ($p \leq 0.05$).For the supraglenoid, there was a significant increase of mean from the younger age groups 18 -28 yrs to 40-50yrs, 18 -28 yrs to 51-61yrs, 18 -28 yrs to 62-72yrs, and 29-39 yrs to 51-61yrs ($p \leq 0.05$). In the area of parotid, there was a significant increase in the means from the age group 18 -28 yrs to 29-39 yrs, 18 -28 yrs to 40-50yrs, 18 -28 yrs to 51-61yrs, and 29-39 yrs to 51-61yrs ($p \leq 0.05$). For the mid-masseteric landmark, there was a significant difference between the age groups 18 -28 yrs and 40-50yrs, 18 -28 yrs and 51-61yrs, and 29-39 yrs and 51-61yrs ($p \leq 0.05$). For gonion, there was a significant increase in the means between the age groups 18 -28 yrs and 29-39 yrs, 18 -28 yrs and 40-50yrs, 18 -28 yrs and 51-61yrs, 18 -28 yrs and 62-72yrs, and 29-39 yrs and 51-61yrs ($p \leq 0.05$). For sub M2, there was a significant increase in the mean from the age group 51-61yrs to 62-72yrs ($p \leq 0.05$).

The AUC summarize the overall predictive ability of anatomical landmarks for sex determination (**Table 4**).

Table 3: AUC analysis for Anatomical landmarks parameters

Area Under the Curve	
Test Result Variable(s)	Area
Glabella	.601
Nasion	.768
lateral nasal	.652
lateral supra-labiale (supra canine)	.760
mental tubercle	.696
mid lower lip margin (infradentale)	.635
fronto-temporale	.693
mid-masseteric	.704

DISCUSSION

Sex determination using skeletal remains possess a great challenge for forensic experts especially when only fragments of the body are recovered. Forensic odontologists play an important role in sex determination when skull and teeth are the only recovered body remains. Forensic odontologist were part of the core team that were involved in solving the recent murder case that had sent shock waves across the country.

The current study is novel as it adapts a newer technology, the ANNas a prediction tool in gender determination which has not been much applied to facial soft tissues in the Indian population. ANN is an upcoming technology in forensic dentistry, that streamlines and automates the method of identification of unknown patterns by minimizing errors. The use of this technology has been explored for gender prediction using skeletal bones like femur, reading facial images, etc.

In the current study, 450 CBCT images were used to determine gender variations based on the maxillary and frontal sinus measurements. In our study, the mean maxillary sinus measurement on both right (17.62 ± 5.38 vs 15.62± 3.85, $p \leq 0.05$) and left sides (18.60± 8.94vs 15.73±3.82, $p \leq 0.05$) were greater in males compared to females. Similar results were observed even for the frontal sinus, wherein males reportedly had larger frontal sinus compared to females (9.41±5.05 vs 5.72±3.44, $p \leq 0.05$). The study by Tambawala SS et al., reported maxillary sinus to be significantly smaller in female patients compared to male patients as assessed by maxillary sinus height (39.71±3.79 vs 30.29±3.34, $p<0.001$), width (29.78 ±2.25 vs 23.80±5.04, $p<0.001$) and length (40.22 ±3.02 vs 35.66±3.84, $p<0.001$)[15].

Further the discriminant analysis demonstrated accuracy of maxillary and frontal sinus measurement to be 70% in both males and females. The morphometric analysis by Kandel S and colleagues reported maxillary sinus measurement accuracy of 72.5% in females and 75% in males based on the discriminant analysis[16].

The present study showed significantly higher soft tissue thickness means in males compared to the females at all the assessed landmarks. The study by De Greef *et al.* on Caucasians and Utsuno *et al.* on Japanese children demonstrated a similar pattern as observed in our study.[17, 18]

In the current study, there was statistically significant differences in the mean FSTT values between males and females at all the craniofacial landmarks except at zygion. Similarly, the study by Chung G-H et al demonstrated statistically significant differences between genders in 16 of the 32 landmarks. Additionally, it was also noted that 51- to 60-year-old age group had the greatest number FSTT peaks (23.83%) followed by the 21- to 30-year-old age group with 19.69%[19].

Further in this study, ANN had accuracy of 72% as assessed on Model 1 on the experimental dataset while Model 2 is likely to be 99% accurate. The study by Priyadarshini D et al conducted to identify gender using the volumetric and linear measurements of maxillary sinuses obtained from a CBCT using ANN based tool reported accuracy of 84.6% with ANN. Further with discriminant analysis, original grouped cases were 96.3% while 95.0% were cross validated(20). The use of several variables and samples in the present study improves sensitivity and specificity of the ANN prediction tool. Further larger studies are warranted to validate our findings.

SUMMARY AND CONCLUSION

Forensic anthropologists are always in an endeavour to improve and develop newer technologies for gender and age estimation using various skeletal bones. Using CBCT scans, we evaluated the morphometric differences in the frontal and maxillary sinuses and differences in FSTT of males and females. Males had larger sinuses and had significantly thicker facial tissues than females. Artificial neural network in our study has shown to be a good gender prediction tool and the study predicting gender using an AI tool showed significant reliability in predicting gender with an accuracy of 72% with model 1 and ~99% with model 2. Hence, application of this technique in the field of forensic sciences is promising as it automates and eases the method of identifying unknown with minimal errors.

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